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Abstract
Extracting information for medical purposes from magnetic resonance imaging is critically important for diagnostic and treatment plans. In this paper, a simple algorithm for tumor segmentation of Magnetic resonance imaging (MRI) is introduced. The novelty incorporates, preserving fine details of the input image while detecting the boundary accurately. Tumor segmentation is carried out by set of pre processing steps followed by morphological operations. Rough contour of the tumor is localized to reduce the search space for the boundary. Line drawing algorithm in cooperated with pixel selection criteria is used to detect the accurate boundary. The algorithm is evaluated in terms of the performance and accuracy with radiologist labelled ground truth MRI scans. Simulation results show that the proposed algorithm provides better identification with above 95% of accuracy, for clearly distinguishable tumors in relation to conventional contour detection methods.

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INTRODUCTION

Image processing in special domain involves producing a set of parameters incorporating the image information using the pixel intensity levels. Magnetic resonance imaging (MRI) and computed tomography (CT) imaging technologies are most profound tools currently used in medical imaging due to their ability to produce vast volume of data with better clarity. Image intensity in MRI depends upon four parameters namely proton density (PD), T1, T2, and T2 relaxation [6]. Images produced by MRI are in high quality with outstanding resolution and contrast for different tissues in any tissue plane. Hence it plays a key role in identifying deformities in soft tissues due to the great contrast over CT imaging [2]. Both horizontal and vertical slices can be obtained through MRI image slices which could aid the abnormality detection in human body parts.

A mass of abnormal cells in the brain that grows inside the restricted space of the skull is diagnosed as a brain tumor [1]. Since these tumors arise in different sizes and shapes with varying positions it is vitally important to detect them using medical imaging technology. Segmentation is the process in which an image is divided into its constituent objects or parts aiming to simplify the image representation to analyze easily [6]. Yet manually detecting brain tumors by trained expertise like radiologist is cumbersome, time consuming and requires constant human inspection. Further the final result biased to individuals [3]. Segmentation process is more complicated when normal tissues are overlapped with tumor tissues.

Therefore automating or semi automating the segmentation process is important and accurately locating the boundary to retrieve valuable information is highly essential.

A boundary is a contour in the image plane that represents changes in pixels from one object to another [5]. Boundary reveals information regarding the outline and shape of the object precisely [4]. Conventional brain tumor segmentation methods include thresholding and region based approaches. Calculation of local threshold is based on prior knowledge or mean intensity value. Various segmentation techniques that utilize different thresholding techniques are present in literature [7]. For instance, in [8] G. Evelin Sujji, Y.V.S. Lakshmi, G. Wiselin Jiji adopts global and adaptive iterative thresholding techniques to segment the tumor from the background. K. A. K. I. S. N. Alyaa and H. Ali suggested an enhanced thresholding method for the segmentation based on the region of interest specified by the user [10]. Further, partial volume calculation of each region is used to identify the thresholding value of each region [14]. Statistical based approach relying on Gaussian distribution to determine threshold value is addressed by A. Stadlbauer, et al. [15]. In the study of Automated segmentation of MR images of brain tumor involves template driven segmentation mechanism using statistical classification process aided by a anatomic atlas [16]. As a modified region growing method, Y. M. Salman [17] has introduced a technique to detect 3D volume accurately adopting hole filling after segmentation. Multi scale transformation and user defined hierarchical watershed segmentation methods have been discussed [18,19] as means to avoid over-segmentation.

Moreover, application of fuzzy c means clustering to segment tumors involves providing better results for overlapping regions in compared to k means clustering [20]. Atlas-based methods incorporate patient specific information from different MRI modalities to segment the brain tumor [21].

The proposed method focuses on precise boundary extraction in contrast to conventional tumor segmentation approaches. The novelty incorporate reliable edge detection, which eliminates possible distortions occur in extracting the tumor region. Further, the method is simple and reduction of search space to a promising region result in increased performance. Thus, the tumor boundary extracted from this system is considerably reliable as an automated system. The derived information can be used to estimate the area and the volume of the tumor accurately .The results presented justify the accuracy of the proposed algorithm. The paper structure flows as three main sections, namely, methodology, results, discussion and conclusion.

METHODOLOGY

Numerous strategies have been proposed in literature for extracting tumors from MRI images. Available segmentation methods such as thresholding, region growing, clustering, Markov random field (MRF) and artificial intelligence approach are discussed in [11].

In the approach presented in this paper, the intensity based technique is adopted for the segmentation. Fig. 1 shows the computational steps of the proposed algorithm. Slice of raw axial MRI is taken as input to the system. It is enhanced using Gaussian low pass filter with an adaptive size. Then the tumor is segmented using morphological operations. This segmented image is used to estimate the initial contour. In the next step feature extraction is performed for the developed algorithm with respect to the selected search area of the tumor. Finally, tumor boundary is identified by using the proposed algorithm. A tumor MRI set related to a patient consists of set of cross sections of brain taken at different phases. Hence, all the above set of steps is repeated to all the slices in a multi slice MRI to obtain a complete three-dimensional segmentation.

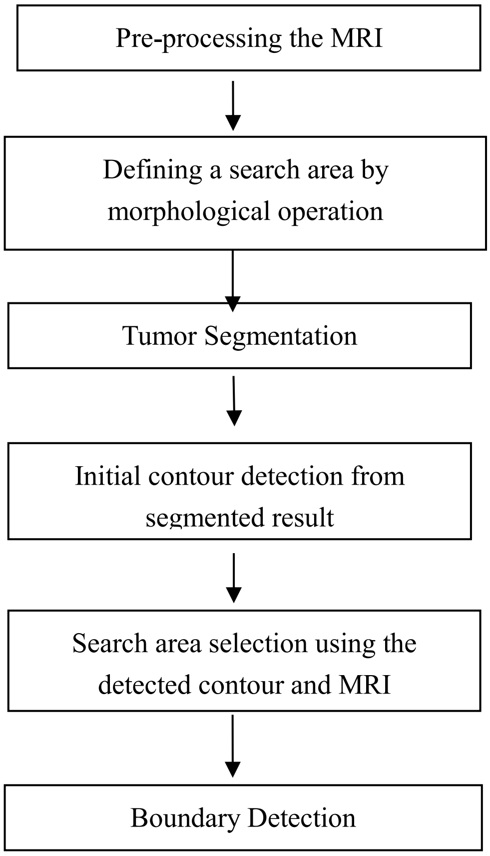


Fig 1 Block diagram for the proposed boundary detection system

Various types of tumor images comprising different shapes and sizes were used to assess the performance of the algorithm. The performance of the proposed algorithm was evaluated by comparing the output image against ground truth labelled image. The accuracy of the system was further tested using the opinion of a radiologist.

A. Tumor segmentation

The Segmentation isolates the cancer cells from non-cancer cells in the background. Tumor segmentation is inherently difficult, since normal cells are overlapped with cancer cells towards the boundary. In the segmentation process the MRI is dived into distinct regions till the tumor is separated from the background. The segmentation phase comprised of two steps, namely; preprocessing of the MRI and applying morphological process. This process is light weight, efficient, and results in a rough initial segmentation.

The extracted rough boundary contains low details with considerable distortions resulted from the morphological operations. In the proposed method, in order to determine the exact tumor boundary a rough contour is sufficient. So the implemented system is not affected by the cell overlapping phenomenon.

1) Preprocessing

Once MRI data are acquired, preprocessing is done to enhance the fine details of the interested area by applying noise reduction algorithms. After the preprocessing the resultant image can be handled more efficiently. Initial MRI is preprocessed to enhance the quality by removing the noise in the image. Gaussian filter is applied to remove the high frequencies and smooth the overall image. The ability of the Gaussian filter to removes the noise without deforming the edges is an added advantage for the task. Global threshold method is applied after the preprocessing of initial gray scale MRIs. Then the gray scale MRI is converted to binary image using the intensity level obtained from global thresholding operation. In the binary image black pixels denote the background while white pixels denote the foreground. Here, optimal global thresholding Otsu's method is used, since it is easy to implement and provides better results which roughly separate tumor parts from the rest.

2) Morphological process

Mathematical morphology is used to analyze a binary image by using simple mathematical concepts. In order to segment the tumor from the binary image dilation followed by erosion is applied. By dilating the binary image foreground is expanded with respect to the binary mask. In this proposed system, several structuring elements were tested with respect to the output. Finally, disk structuring element was used as the most compatible shape with adaptive sizes. Next by eroding the image the foreground was shrunk according to the shape and size of the disk structuring element. Finally hole filling algorithm was applied to remove unwanted small areas contained in the tumor binary image.

B. Boundary detection algorithm

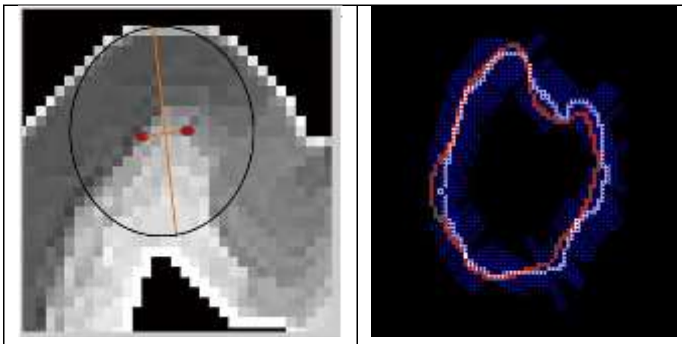
After isolating the tumor region a rough boundary of extracted tumor was used as the initial contour. The search space for the exact contour detection was optimized by limiting the search area to neighboring locations of the initial contour.

1) Pixel selection algorithm

Starting from two of the initial contour pixels a perpendicular line was drawn to pick the two ending points as shown in Fig 2 a. The width of the line is chosen by considering the area which is suspected to contain the edge point of the boundary. A line drawing algorithm Digital Differential Analyser (DDA) [13] was used to select the pixels for the gradient scale, employing the previously selected two end pixels. This set of pixels was treated as a promising area which contains the exact edge point corresponding to that region. Similarly the entire feature points were selected in this manner for the proposed algorithm.

2) Boundary manipulation algorithm

Starting from the initial contour set of pixels from two adjacent locations was selected as a gradient scale as the input to the proposed algorithm. The correct edge location was calculated by considering the average value. First the average of pixel intensity value set was determined. Then each average value was selected as the boundary point of the tumor. The obtained resultant points were plotted over the MRI image as the exact tumor boundary. To evaluate the accuracy of the algorithm this was compared against labelled "ground truth" scans. Fig 2 b shows the search area selection for the input of the proposed algorithm. The initial contour is indicated in white color. Pixel points of the search area are indicated in blue color.



(a) End point selection	(b) search area selection

Fig 2 Search area selection & Search area of intensity pixel scale generated from initial contour of MRI image

Fig 3 indicates the segmented tumor by applying preprocessing and morphological operations. The localized tumor is used to extract the initial contour as the input to the proposed algorithm. Canny edge detection method is applied as it improves the signal to noise ratio of the output and provides a better detection of edges even in noisy environment.

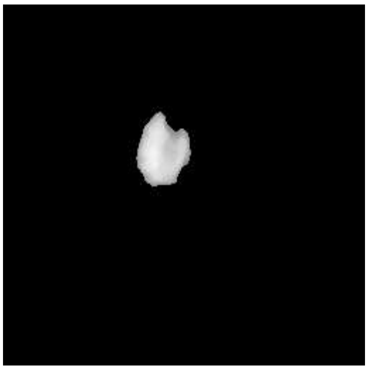


Fig 3 Tumor segmentation result of a MRI

After extracting the rough boundary the segmented tumor search area is selected as explained in the step B in methodology. The algorithm is optimized by restricting the search area around the initial contour without manipulating the whole MRI scan.

The initial rough boundary was used as a starting point and the gradient level of the search area is checked and evaluated to adjust the boundary accurately. The adjustments were made by considering the gradient level variation in the search space with respect to the considered boundary point.

RESULTS AND DISCUSSION

The main aim of the proposed system is to detect the tumor boundary precisely and efficiently. The MATLAB R2015 was used to implement the system.

The proposed system was tested with sample MRI images given in Fig 4. In order to evaluate the performance, standard indicators of specificity, sensitivity, accuracy and elapsed time are used [12].

Tumor isolation followed by contour detection for sample dataset is presented in Fig 4-6.

Fig. 4 showcase the sample MRI data used to test the developed algorithm. It can be seen that tumors of various shapes and sizes were selected to evaluate the proposed algorithm. Fig. 5 indicates the extracted initial contour for the three sample MRIs. The images were preprocessed and mathematical morphological operations were applied to localize the rough boundary as explained in step A in the methodology. Fig. 6 illustrates the result of boundary extraction by applying the proposed algorithm. The detected boundary is outlined in the original MRI image in red color. The final boundary was evaluated for the accuracy of the output by comparing the results with the expected tumor boundary obtained by an expert through visual inspection.

The results tabulated in table 1 shows the values of the performance indicators of the developed system. To obtain these results the segmented image is compared with a reference image. The accuracy of boundary pixel selection is evaluated by adopting pixel wise criteria. The segmentation results in true positives (TP) which are correctly segmented as foreground compared to the actual tumour mask as well as false positives (FP) where the pixels of the output is falsely segmented as foreground. True negatives (TN) include pixels correctly segmented as background. False negative (FN) pixels comprised of segmentation areas falsely recognised as background.

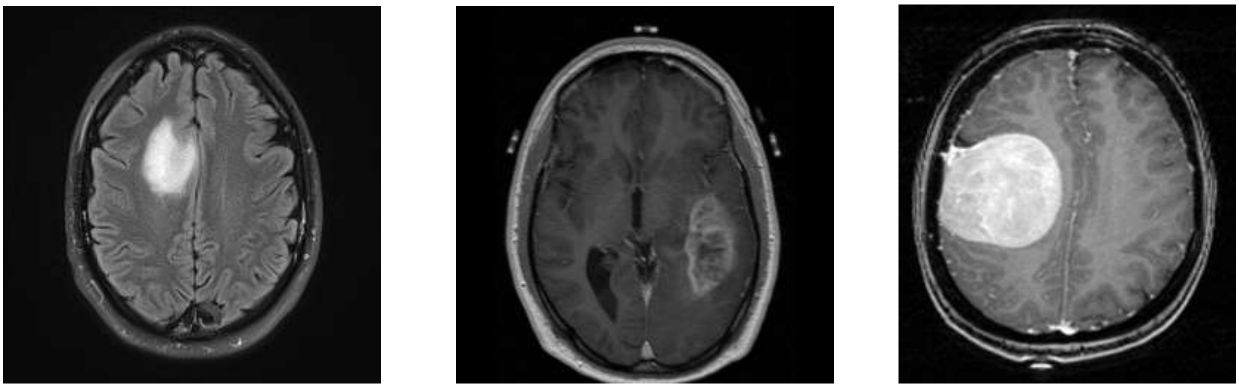
Sensitivity is an indicator representing how well the system performs the identification process and is determined as a proportion of actual positives to the total[9].

$$Sensitivity = \frac{TP}{(TP + FN)} \qquad (1)$$

Accuracy is determined as the proportion of correctly segments areas with reference to the original tumor mask. The percentage value indicates the correctness of the segmentations process, and precise segmentation is indicated by the accuracy values is 100%.

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \qquad (2)$$

Time taken for the whole segmentation process is determined by the elapsed time in seconds. The time is measured as the using the system clock run in MATLAB environment to produce the final results in 1.7 GHz Core i3 processor.



(b) (c)

Fig 4 : Sample tumor images Tumor A, Tumor B and Tumor C

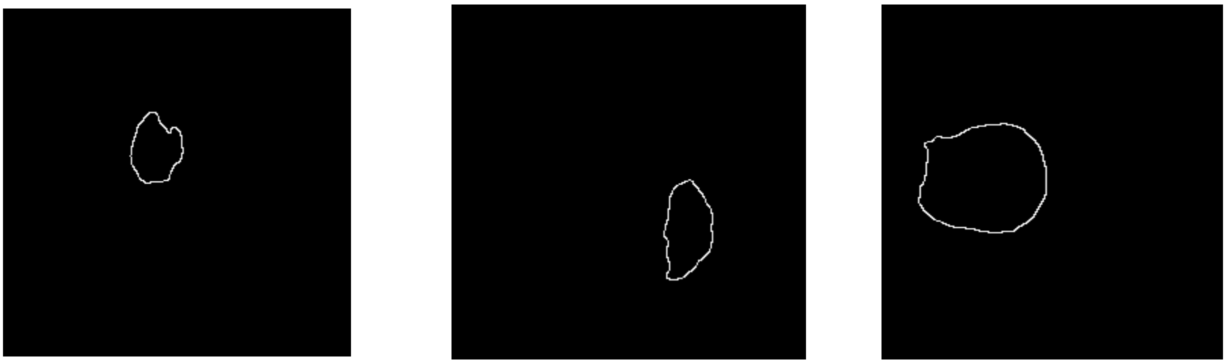


Fig 5 : Initial contour extraction

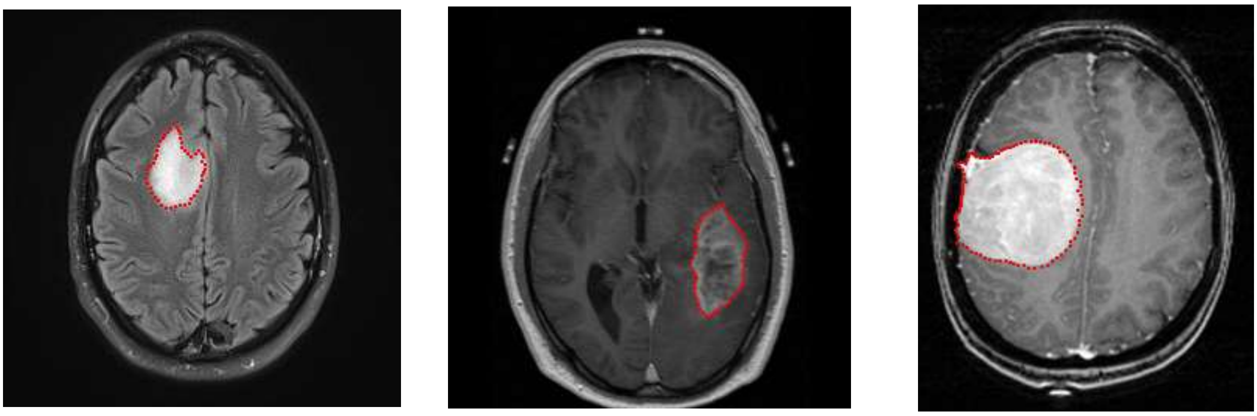


Fig 6 : Final result of detected tumor edge

TABLE I

PERFORMANCE INDICATORS OF THE PROPOSED SYSTEM

image	**accuracy**	**sensitivity**	**Elapsed time (s)**
a	0.9891	0.9601	3.86
b	0.9623	0.8862	2.77
c	0.9905	0.9833	3.03

According to the obtained results the more prominent the tumor is the higher the values of accuracy, sensitivity and elapsed time. Tumors such as MRI (a), (c) which display clear distinction from the background could be recognized easily and accurately. In the MRI image (b) the indicated tumor comprised of more fuzzy edges thus the performance indicated low values compared to others. The elapsed time is higher for the segmentation process becomes higher with the low image quality. From the results it is evident that the proposed system provides clear boundary detection and it can be used as an aid for further treatments.

However, the proposed system performs poorly when the noise level of the MRI is high as it directly affect to the morphological operations while extracting the fuzzy edges of the tumor. Moreover using Otsu's method provides ambiguous results when the image quality is considerably low. Hence, thresholding in a more adaptive manner might enhance the accuracy. Multi level image threshold mechanism provided by Matlab performs well with the Otsu's method and helped to overcome with the adaptive threshold selection.

CONCLUSION AND FUTURE WORK

In this paper, a novel algorithm is introduced to detect the tumor boundary more accurately as a guiding aid for medical practitioners. The system identifies the tumor boundary with higher accuracy level for the tumors with clear distinction from the background. Thus the tumor boundary extracted from this system is considerably reliable than conventional edge detection methods as an automated system. The system can be further modified for the tumors which are having more fuzzier edges. By far deep neural networks, in particular convolution networks are rarely used in boundary detection problems. Hence, in future such neural networks can be proposed for this state of art application. Further this system can be extended for 3D boundary detection of brain tumors.

REFERENCES

1. Sridhar, D., and IV Murali Krishna. "Brain tumor classification using discrete cosine transform and probabilistic neural network." *Signal Processing Image Processing & Pattern Recognition (ICSIPR), 2013 International Conference on*. IEEE, 2013.
2. Othman, Mohd Fauzi, and Mohd Ariffanan Mohd Basri. "Probabilistic neural network for brain tumor classification." *2011 Second International Conference on Intelligent Systems, Modelling and Simulation*. IEEE, 2011.
3. Aslam, Asra, Ekram Khan, and MM Sufyan Beg. "Improved Edge Detection Algorithm for Brain Tumor Segmentation." *Procedia Computer Science* 58 (2015): 430-437.
4. M. R. Udhaya, "Boundary Exposure using Intensity and Texture Gradient Features," *IOSR Journal of Computer Engineering (IOSRJCE)*, vol. 8, no. 1, pp. 28–33, 2012.
5. J. Anand and K. Sivachandar, "An Edge Vector and Edge Map Based Boundary Detection in Medical Images," vol. 1, no. 4, pp. 1050–1055, 2013.
6. G. Latif, S. B. Kazmi, M. A. Jaffar, and A. M. Mirza, "Classification and Segmentation of Brain Tumor Using Texture Analysis," *Recent Adv. Artif. Intell. Knowl. Eng. Data Bases*, pp. 147–155, 2010.
7. S. Z. Oo and A. S. Khaing, "Brain Tumor Detection and Segmentation Using Watershed Segmentation and Morphological Operation," *IJRET Int. J. Res. Eng. Technol.*, vol. 3, pp. 367–374, 2014.
8. G. E. Sujji, Y. V. S. Lakshmi, and G. W. Jiji, "MRI Brain Image Segmentation based on Thresholding," *Int. J. Adv. Comput. Res.*, vol. 3, no. 8, pp. 1–5, 2013.
9. S. Mohane and M. Borse, "Comparitive Study of Brain Tumor Detection Using," pp. 422–428, 2015.
10. K. A. K. I. S. N. Alyaa H. Ali, "Segmentation of brain tumour using Enhanced Thresholding Algorithm and Calculatethe area of the tumour\n," *IOSR J. Res. Method Educ.*, vol. 4, no. 1, pp. 58–62, 2014.
11. S. Egmentation, D. L. Pham, C. Xu, and J. L. Prince, "Current Methods in Medical Image Segmentation," 2000.
12. P. Tambe, "Comparative Study of Segmentation Techniques for Brain Tumor Detection," vol. 5, no. 2, pp. 269–271, 2016.
13. Gonzalez, Rafael C., and Richard E. Woods. "Digital image processing."*Nueva Jersey* (2008).
14. Y.-C. Sung, K.-S. Han, C.-J. Song, S.-M. Noh, and J.W. Park, "Threshold estimation for region segmentation on mr image of brain having the partial volume artifact", in Signal Processing Proceedings, 2000. WCCC-ICSP 2000. 5th International Conference on, IEEE, 2000, vol. 2, pp. 1000-1009.

15. A. Stadlbauer, E. Moser, S. Gruber, R. Buslei, C. Nimsky, R. Fahlbusch, and O. Ganslandt, "Improved delineation of brain tumors: An automated method for segmentation based on pathologic changes of 1H-MRSI metabolites in gliomas", vol. 23, no. 2, pp. 454-461, 2004.
16. M. R. Kaus, S. K. Warfield, A. Nabavi, P. M. Black, F. A. Jolesz, and R. Kikinis,"Automated segmentation of mr images of brain tumors", vol. 218, no. 2, pp. 586-591, 2001.
17. Y. M. Salman, "Modified technique for volumetric brain tumor measurements, Journal of Biomedical Science and Engineering" , vol. 2, p. 16, 2009.
18. R. Roslan, N. Jamil, and R. Mahmud, Skull stripping magnetic resonance images brain images: Region growing versus mathematical morphology, International Journal of Computer Information Systems and Industrial Management Applications, vol. 3, pp. 150-158, 2011
19. J. E. Cates, R. T. Whitaker, and G. M. Jones, Case study: An evaluation of user-assisted hierarchical watershed segmentation, Medical Image Analysis, vol. 9, no. 6, pp. 566-578, 2005.
20. J. C. Bezdek, Pattern Recognition with Fuzzy Objective Function Algorithms. Kluwer Academic Publishers, 1981.
21. N. Moon, E. Bullitt, K. Van Leemput, and G. Gerig, Automatic brain and tumor segmentation, in Medical Image Computing and Computer-Assisted Intervention—MICCAI 2002. Springer, 2002, pp. 372-379.